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Rainfall variability and food crop portfolio choice: evidence from Ethiopia

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Abstract This paper concerns the patterns of food crop choice in a multicropping setting, in which production risk considerations and rainfall uncertainty are likely to be critical factors. The analysis employed plot level panel data from Ethiopia, combined with 30 year meteorological data corresponding to the survey villages used to construct seasonal and yearly rainfall variability. Using the single index approach, the riskiness of crop portfolio was constructed at a household level, taking into account the multicropping nature of the farming system. The combined riskiness of crops grown at a household level responded negatively to annual rainfall variability, with seasonal rainfall variability having a less consistent impact. Farmers are, therefore, more likely to select less risky crop portfolios even when intercrop interactions are taken into account.

Keywords Crop choice · Risk index · Ethiopia · Annual and seasonal rainfall variability

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Introduction

The existence of pervasive risks in agriculture tend to alter behaviour in ways that at first glance seem suboptimal and make farmers less willing to undertake activities and investments that have high expected outcomes (e.g. Rosenzweig and Binswanger 1993; Yesuf and Bluffstone 2009). As part of self insurance measures, farm households alter the composition of productive and non-productive asset holdings in response to their anticipation to different degrees of weather risk and other production risks (Isik 2002). Conservative methods for crop production, such as diversification into less profitable but less risky crops is one such ex-ante risk coping mechanism (Benin et al. 2004; Morduch 2002). This is particularly true with regards to hedging against weather risk (Kurukulasuriya and Mendelsohn 2006).

Given the pervasiveness of weather uncertainty and the almost exclusive dependence of smallholders on rainfall for productivity, a number of studies have looked into the nature and degree of crop riskiness in relation to the presence of production and market risks (e.g. Fafchamps 1992; Haile 2007; Dercon 1996).[1] It should be noted, however, that

[1] Although the focus of the paper is on the role of crop diversification as a mechanism of coping with weather risk, crop diversification could have other important purposes. In a situation where output markets work perfectly, production decisions are based solely on input and output price considerations and farm household consumption decisions are recursive to production decisions With imperfect output markets, however, there is imperfect substitution between market and home production, and recursive consumption decisions do not hold. Instead, the production and consumption decisions are made simultaneously and hence there is non-separability in production and consumption (de Janvry et al. 1991). Indeed, output market integration is identified as critical in the decision of households to diversify their crop choices (Van Dusen et al. 2007). This could be because, to the extent that the particular goods demanded by households are not available in the market, households will be forced to own-produce the goods. In addition, some varieties might have consumption qualities favored by particular localities but may not be widely produced and may have limited availability in the market which would prompt own production (Smale 1995).

these previous studies either relied on subjective measures of the riskiness of the crops or focussed on selected, mainly major types of crops.

A more objective way of measuring the riskiness of individual crops and aggregating them (in a multicropping setting), would enable an accurate measurement of the contribution of individual crops to the riskiness of a crop portfolio, incorporating the mutual interdependence across crops at a farm household level. Accordingly, the aim of this paper is to investigate the riskiness of a combination of crops at a farm household level in relation to rainfall variability. We use a method of measuring and aggregating crop riskiness applied to farm management studies. In particular, we follow Turvey (1991) in measuring individual crop risk and portfolio risk using the so called Single Index Model. We use plot level data from the Sustainable Land Management Survey covering four rounds collected in the years 2000, 2002, 2005 and 2007 in the Amhara National Regional state of Ethiopia. The data contain production information by plot. This allows estimation of both plot (crop level) riskiness as well as farm household level crop portfolio riskiness by aggregating the individual crop riskiness measures.

The rest of the paper is organized as follows. A review of the literature on crop choice and weather uncertainty is provided in "Crop Choice in Agricultural Risk Management and Weather Shocks" section. "Site Description and Data" section provides background information on data and variables employed in the empirical analysis. The estimation procedure is provided in "Estimation Procedure" section. "Results and Discussion" section reports the results and "Conclusions" section concludes the paper offering some policy implications.

Crop choice in agricultural risk management and weather shocks

Understanding the responsiveness of crop portfolio choice to seasonal and annual rainfall variability is very important in developing countries. Weather variability has tremendous impacts on the performance of agriculture and most of the farm households have experienced drought and flood. Moreover, precautionary saving is very difficult and public safety nets and financial markets are imperfect. The combination of production environment and low adaptive capacities restrict the number of actions that can be implemented (Rosenzweig and Parry 1994; Reilly 1996; Reilly and Schimmelpfennig 1999; Kates 2000; Kurukulasuriya et al. 2006; Seo and Mendelsohn 2008; Deressa et al. 2009). Farmers thus have a very limited range of strategies that can be used as mechanisms to manage risk (Barrett et al. 2007; Dercon 2002; Morduch 2002). Households mostly rely on crop choice decisions to hedge against weather risk (Kurukulasuriya and Mendelsohn 2006, Rosenzweig and Parry 1994).

In a pioneering study of crop choices under multivariate risk, Fafchamps (1992) showed that crop diversification, an important feature of smallholder farmers in developing countries, is a response to high variance in food prices, and other risks that are poorly insured against. Similarly, using data from Pakistan, Kurosaki and Fafchamps (2002) showed that farmers' crop choices are dependent on price and yield risk. Crop diversification via both crop sequencing and rotation is another mechanism whereby soil moisture content and nutrients are altered and intra-yield fluctuations are minimized (Amede et al. 2001; Benin et al. 2004). Similarly, inter-cropping is also a traditional way to restore soil productivity and obtain the maximum return from the cultivated land under uncertain conditions (Corbeels et al. 2000). Planting short season varieties that mature earlier in the season, thus protecting them against the risk of moisture shortage and yield loss is also a common agricultural practice of farmers. Di Falco and Chavas (2009) showed that high diversity levels can reduce downside risk exposure (i.e. the risk of crop failure). Seo and Mendelsohn (2008) and Kurukulasuriya and Mendelsohn (2006) also examined the climate sensitiveness of crop choices using cross country data in Latin America and Africa, respectively.

Understanding crop choice decisions at the household level can help to generate important information on how farm households react to weather related risk by changing the composition of their crop choices.[2] Haile (2007) showed that choosing the crop most suited to a specific rainfall condition is a strategy of farmers to cope with unpredictable rainfall in Ethiopia. In general, crop choice and land allocation decisions were such that in times of low rainfall, the dominant crops chosen tended to be those tolerant of moisture stress, such as grass pea rather than moisture sensitive crops such as wheat.[3] This analysis clearly indentified at the household level how crop portfolio choice is affected by

[2] In low income risk prone settings, crop biodiversity could be a critical resource that ensures efficient use of complementary resources and shields against natural risk. From an ecological perspective, increased species diversity contributes to an ecosystem's performance through overall productivity, stability and facilitative interactions (Hooper et al. 2005 and Baumgartner 2007). Diversity increases productivity through increased likelihood of the presence of key productive species, enhanced complementarity between functionally different species and efficient use of available resources (Aarssen 1997; Loreau 2000). In addition, diversity enhances facilitative interaction between species, whereby certain species alleviate harsh environmental conditions or provide a critical resource for others (Mulder et al. 2001). Furthermore, diversity increases likelihood that species with different sensitivities to fluctuations are present thereby providing overall ecosystem stability (Borrvall et al. 2000).

[3] It should be noted, however, that moisture stress is not the only characteristic that determines the riskiness (beta coefficient) of the crops. For instance, crops such as lentils have a low beta coefficient despite being drought sensitive. Similarly, sorghum and teff have high beta coefficients despite being drought tolerant.

weather risk. However, the analysis was not based on an aggregation of the different crops grown within the household but on decisions as to whether to grow a given crop on a specified plot or not, with the riskiness of the crop measured by the nature of the crop (small cereal, large cereal, pulse).[4]

Site description and data

Ethiopia is one of the least developed countries in the world, with a GDP slightly over 10 billion USD and a population of over 70 million. Agriculture is the main source of livelihood for an overwhelming majority of Ethiopia's population and accounts for about 44 % of total GDP with crop production accounting for 28 % in 2005/6 (MoFED 2006). It is the main source of export earnings and raw materials for local agro-industry. Ethiopian agriculture is heavily dependent on rainfall with irrigation covering only around 1 % of the total cultivated land. Small-scale and subsistence farming is predominant. Given the nature of farming in Ethiopia, the amount, geographic and temporal distribution of rainfall and temperature are very important determinants of crop production. This has been demonstrated by the devastating effects of droughts which led to the death of close to a million people in 1984 and several other recurrent droughts over the years. Rainfall variability and associated drought have been major causes of food shortage and famine in Ethiopia (World Bank 2008)

Information was collected through a rural household survey conducted by the Ethiopian Development Research Institute and Addis Ababa University in collaboration with Gothenburg University, and through financial support from the Swedish International Development Agency (Sida). The survey sites included households in two Zones (South Wollo and East Amhara) of the Amhara National Regional State, a region that encompasses part of the Northern and Central Highlands of Ethiopia, and was conducted on the same households in the 2000, 2002, 2005 and 2007 cropping seasons. The rainfall data obtained from the Ethiopian Meteorology Authority included monthly rainfall data from the years 1976–2006, collected in stations close to the study villages (*kebeles*).

The farming system is a mixed crop-livestock system, with a given household having several field plots for crop cultivation, and livestock grazing mainly on communal fields.[5] The crop production system consists of cereals, legumes, oil seeds and others. The major cereal crops include *teff*, wheat, barley, sorghum and maize. Legumes include several kinds of beans and peas as well as lentils and vetch. Perennials include coffee, fruit trees (orange, mango, papaya, banana, avocado, guava, and pineapple) and spices.[6] Cereals were the major crops grown in the study area followed by legumes. Oil crops formed a smaller share of the crops grown, followed by vegetables, spices, perennials and much smaller quantities of other plants. Table 1 presents a description of the variables and their descriptive statistics. It should be noted that as the regressions were based on household and not plot level observations, all the variables were household level or averaged at a household level.

Variable definition

One of the objectives of the paper was to generate a measure of crop portfolio riskiness at a household level by using the riskiness measures of individual crops and combining them into a measure of riskiness at a household level. To this end, we used the Single Index measure, developed by Turvey (1991). The Single Index approach enables derivation of coefficients corresponding to the riskiness of each crop based on information on their corresponding revenues. The approach, as applied to crop portfolios, works under the assumption that revenues associated with various farm enterprises are related only through their covariance with some basic underlying factor. Two measures form the basis of the single index method- the stochastic individual crop revenues, and the reference portfolio, which is the sum of individual crop revenues. Equation 1, gives the econometric relationship between the reference portfolio, S_{Kh}, and the individual crop revenues S_{ih} for the i^{Th} crop and h^{Th} household

$$S_{ih} = \alpha_i + \beta_i S_{Kh} + e_{ih} \qquad (1)$$

Where α_i is the intercept and β_i is the regression coefficient, and e_{it} is the error term.[7] Table 2 presents the beta coefficients (β_i is the regression coefficient in Eq. 1) corresponding to the crops grown by the sample households. Crops like white teff, wheat, maize, sinar, beans, vetch, have higher levels of beta

[4] Dercon (1996) argued that about 90 % of the difference in land allocation (to risky and less risky crops) between the poorest and the wealthiest groups of households was shown to be the result of asset differences. This result is also consistent with the study of the choice of investment portfolio in rural India conducted by Rosenzweig and Binswanger (1993).

[5] Livestock, while theoretically part of the portfolio, are not included in our analysis (They are, instead, used as a control representing the wealth levels of households). The major reason for this is the difference in the decision time frame that involves choosing crop types and livestock. Crop production is a seasonal choice while livestock is a much longer term investment (seen by many as a way of saving, and an important component of agricultural input (particularly oxen)).

[6] It should be noted that, while households diversify their crop choices, all the crops do not necessarily coexist in the same households. This is particularly attributed to the different crops being grown in different elevation belts commonly known as Dega (high elevation), Woina Dega (medium elevation), and Kola (low elevation).

[7] For details on the derivation of the single index measure and differences in the nature of the data used in Turvey (1991) and our analysis, see Appendix 1.

Table 1 Description of variables used in the regressions

Variable	Description	Mean	St.d.
Socio economic characteristics of the household			
Gender	Gender of the household head	0.182	0.386
Age	Age of household head	50.461	16.224
Write	Head's formal education (1=read and write; 0=otherwise)	0.362	0.481
Adult male	The number of male working-age family members of the household	1.902	1.194
Adult female	The number of female working-age family members of the household	1.815	1.021
Oxen	The number of oxen	1.982	1.371
Livestock	The number of livestock (in tropical livestock units)	5.387	4.419
Physical farm characteristics of the household			
Land area	Total farm size of the household in hectares	1.414	1.310
avg_fertile	Proportion of highly fertile plots in the total plots managed by the household	0.413	0.373
avg_red	proportion of red soil plots in the total plots managed by the household	0.511	0.373
avg_flat slope	proportion of plots with zero slope in the total plots managed by the household	0.676	0.337
Time variant variables (averaged over the survey years)			
mean_female	Number of female adults averaged over years	5.769	8.719
mean_male	Number of male adults averaged over years	8.341	29.180
mean_ox	The number of oxen averaged over years	1.952	1.082
mean_livestock	The number of livestock averaged over years	1.841	0.867
Rainfall variables			
Annual mean	Long term annual mean rainfall (by survey year)	1486.595	489.7908
summer mean	Long term summer mean rainfall (by survey year)	115.3839	56.20756
spring mean	Long term spring mean rainfall (by survey year)	188.1526	70.11675
Dependent variables			
Riskiness Index	The average of beta coefficients for each of the crops grown within a household.	0.458	0.315
Risk ranking	The sum of risk ranks attached to each of the crops grown within a household	0.864	0.542

Table 2 Beta coefficients by crop type

Crop type	Scientific name	Beta coefficient	Crop type	Scientific name	Beta coefficient
White teff	Eragrostis tef	0.154	Lentils	Lens culinaris	0.078
Mixed teff	Eragrostis tef	0.141	Vetch (guaya)	Viciadasycarpa	0.311
Black/red teff	Eragrostis tef	0.040	Chickpea(shimbra)	Cicer arietinum	0.06
Wheat	Triticum aestivum	0.062	Gibto	Lupinus albus	0.349
Barley-gebs	Hordeum vulgare	0.046	Potatoes	Solanum tuberosum	0.181
Maize - bekolo	Zea mays	0.073	Pepper	Piper nigrum	0.512
Sorgum	Sorghum bicolor	0.183	Fenugreek-abish	Trigonella foenum-graecum	0.041
Millet-zengada	Panicum miliaceum	0.014	Coffee	Coffea arabica	0.426
Oats - aja	Avena sativa	0.019	Chat	Catha edulis	0.181
Sinar - gerima	Sinapis arvensis	0.126	Grass	Digitaria ischaemum	0.241
Beans	Vicia faba	0.071	Ecualyptus	Eucalyptus globus	0.220
Cow peas - ater	Vigna unguiculata	0.070	Other crops		0.233

coefficients while mixed teff, chickpea, gibto, potatoes, and a collection of all other minor crops have considerably lower levels of beta coefficients.[8] There were also considerable differences in beta coefficients between crop categories. Crops such as potatoes, vetch and gibto have high beta coefficients (above 0.3) while lentil, linseed, oats and millet have very low beta coefficients (below 0.01).

The interpretation of the beta coefficients is as follows. For example, the beta coefficient of barley 0.046 compared to that of white teff of 0.154 suggests that a 1 Birr increase in expected revenues for a representative household's portfolio implies a 0.046 Birr increase in expected barley revenues, whereas a similar increase in teff implies an increase of 0.154 Birr. This implies that the revenues of white teff have proportionately more variance than the revenues for barley by about three times the amount. Crops with the smaller beta coefficient have a more stabilizing effect on the overall farm household revenue than crops with higher beta coefficients.

*The risk index (*portfolio beta) is computed as the average of the beta coefficients for each of the crops grown within a household. For instance for a household growing teff, maize and beans,[9] an average beta will be 0.207, which is the average of 0.154, 0.016 and 0.451 for the three crops respectively. The risk of this portfolio is substantially higher than a portfolio beta (risk index) of, say, 0.1 for a household growing a combination of red teff, barley, maize and potatoes.

For comparison purposes we used an additional risk measurement method using simple ranking, which we call *risk ranking*. To compute this measure, all the crops were categorized into three risk groups and numbers were attached to each of the crops grown within the household, a higher number reflecting higher riskiness and vice versa. *Risk ranking* is calculated by summing these numbers. While this measure might not capture riskiness in a systematic manner and is not necessarily well founded in theory, it is simpler and more transparent and could be used in other cases where relatively extensive data might not exist, as would be the case in most developing countries where multicropping farming is practised.

The rainfall data was obtained from eight meteorological stations close to the 12 study villages. In consultation with the Meteorology Authority, the rainfall values assigned to the villages were based on proximity. The station level meteorological data were interpolated at a household level using farm level latitude and longitude information.[10] We measured climate change using two measures: seasonal and annual mean. Annual rainfall means were measured as the average annual rainfall over years 1976–2006. We chose the spring (*Belg*) and the summer (*Kiremt*) months in the seasonal measures as they correspond to the minor and major rainy seasons respectively.[11] Accordingly, the average Kiremt rainfall measure includes the mean rainfall values for the 26 years in the Kiremt season. Similarly, the Belg (spring) rainfall average is measured as the mean of the rainfall values for the spring months.

The average age of respondents was 47 and 19 % of households were female headed. Literacy was 39 % and the ratio of male to female adult members within households was 2:1.9. This is not surprising considering that there are limited off-farm opportunities and limited mobility out of agriculture in the study area and in rural Ethiopia in general. The average livestock holding was 5.18 units (tropical livestock units)[12] and oxen ownership averaged 1.87 per household. Average land holding per household in the area was around 1.18 ha. The proportion of fertile plots was 0.42 with zero slope, as opposed to steeper sloped plots, which were 0.67.[13]

Estimation procedure

The aim of this section is to set up a framework for analyzing the link between the riskiness in crop composition grown by a household and rainfall variability. We frame our analysis under the standard theory of portfolio choice, where the problem facing a representative risk averse farm household is to choose an optimal mix of crops (crop diversity) in order to maximize expected return at the end of the production period, given the production function and land, labour and other resource constraints (Benin et al. 2004). Assuming that the utility function is state independent, solving such a portfolio choice problem would give an optimal portfolio choice function, the estimable form of which is given by Eq. 2.[14]

$$r_{ht} = \beta x_{ht} + \gamma v_{ht} + \alpha_h + \xi_{ht} \tag{2}$$

[8] Due to the difficulties of limited numbers of observations in obtaining sensible estimates for the crop riskiness measures of minor crops, theses were put into the "other" group category. Hence, any household growing one or more of these minor crops would have the beta risk coefficients calculated based on groupings in the "other" category.

[9] As the beta regression is based on yield, the area allotment is taken into account as the denominator of the dependent variable in Eq. 1.

[10] The thin plate spline technique was used for interpolation, the coding of which was done in the statistical programming software, R.

[11] M*eher* season (approximately June-September) crops harvested in September-December make up the bulk of food production (90–95 %), the *belg* is the short rainy season, which extends from February to May and *Belg* production typically accounts for only 5–10 % of total annual production (CSA 2001).

[12] The tropical livestock units are given weights based on the type of livestock reported by the household. The weights range from 1.25 for a horse to 0.125 for chicken.

[13] The soil types identified in the survey were fertile, medium fertile and infertile. In addition the soil colours were categorized as red, black and white (grey). In the analysis, we added fertile and red soil categories using the other categories as baselines.

[14] For details on the derivation of the estimable equation, see Di Falco and Chavas (2009).

where 'ht' refers to farm household h in period t. Farm household level riskiness of crop portfolio at time t is denoted by R_{ht},[15] X_{ht} represent the socio-economic and farm level characteristics and V_{ht} stands for weather related variables at time t. The parameters α, β, and γ represent the respective vector of parameter estimates and ξ_{it} represents the error term. The composite error term $\xi_{it} = \alpha_i + u_{it}$ is composed of a normally distributed random error term $u_{ij} \sim n(0, \sigma_u^2)$ and unobserved household specific effects α_h.

Under the assumption that α_h is orthogonal to the observable covariates a random effects estimator could be employed as an effective estimator of Eq. 2 (Baltagi 2001; Wooldrige 2002). However, allowing an arbitrary correlation between α_h and the regressors/observed covariates, requires a fixed effect as it takes α_h to be a group specific constant term and uses a transformation to remove this effect prior to estimation (Wooldrige 2002).

To remedy the major drawback of removing the household specific effects of the fixed effects estimator, Mundlak (1978) [16] suggest replacing the unobserved effect with its linear projection onto the explanatory variables in all time periods plus the projection error. Allowing for correlation between α_h and x_h and assuming a conditional normal distribution with linear expectation and constant variance implies that α_h can be approximated by the linear function in (3)

$$\alpha_h = \psi + \bar{x}_h + e_h \quad e_h|\bar{x}_h \sim N\left(0, \sigma_\alpha^2\right) \tag{3}$$

where $\bar{x}_h$ is the average of the time varying variables in x_{ht} and σ_e^2 is the variance of e_h in Eq. 3. Substituting the expression in Eq. 3 for α_h in Eq. 2 gives:

$$r_{ht} = \beta x_{ht} + \gamma v_{ht} + \psi + \bar{x}_h + \theta_{ht}, \quad \theta_{ht} \sim N\left(0, \sigma_\theta^2\right) \tag{4}$$

This approach of adding the means of time varying observed covariates as controls for the unobserved heterogeneity without the data transformation in the fixed effects estimator is commonly known as the pseudo fixed effects or the Chamberlain-Mundlak's Random Effects Model (Wooldridge 2002).

Results and discussion

In this section, the results based on the regressions in Eq. 2, representing the random effects specification, and Eq. 4, representing the Chamberlain-Mundlak's random effects specifications are discussed. The results of these two specifications are presented in the first and second panels in Table 3, respectively. Each of the panels presents the results from three regressions and the first column includes annual rainfall availability (as measured by the coefficient of variation of annual rainfall for 26 years), in addition to other control variables. The second regression contains the same set of variables as column 1 in addition to the mean for the major rainy season, *Kiremt*. The third regression contains the same set of variables as column 1 in addition to the mean for the minor rainy season, *Belg*. The chi square results show that the random effects models perform better than the pseudo fixed effects models.

Households experiencing high mean annual rainfall were more likely to have a higher value of riskiness corresponding to their crop portfolio (Table 3). In particular, the coefficient for annual rainfall mean indicates that if the mean increases by 1 unit, the riskiness of the overall portfolio increases by 0.981 units (see Table 1 column 3). Similarly, positive and significant coefficients of the mean of summer rainfall indicate that higher levels of summer rainfall lead to higher levels of risk composition and vice versa. The mean of the spring rainfall, however, appears to have negative effect on the riskiness of the crop portfolio.

The importance of Belg season rainfall on riskiness could be due to the role *belg* rains play in *meher* crop production. *Belg* rains are crucially important for seed-bed preparation for short and long-cycle *meher* crops; and for planting of long-cycle cereal crops (Maize, Sorghum, Millet) that take both the belg and meher seasons to mature (Eggenberger and Hunde 2001), despite *belg* crops contributing less than 10 % of the total grain production (CSA 2001).

Several of the control variables are significant. Of the socio-economic characteristics, age and gender of the household head have negative effects on the riskiness of crop portfolio, implying that older and female headed households are more likely to opt for lower risky combinations of crops, all else being constant. Education increases the variation in risk composition of crop choices across farm households, suggesting that more educated households grew crops with higher combined levels of riskiness. Households with large numbers of adult male and females seem to select riskier crop composition than those with fewer. This could be due to the fact that the family is the most important source of agricultural labour so those households with many members are able to venture into producing riskier and more labour demanding crops.

Households with better resource endowment as measured by livestock also tend to have a riskier portfolio. However, the impact of oxen is less consistent—being either insignificant or negative across estimations. This could be due to the non-uniform draught power requirements of different crops (and their combinations). Most of the physical farm

[15] It should be noted that R_{it} takes two distinct measures in our analysis: the beta coefficient and the risk ranking measure.

[16] It should be noted that the strict exogeneity assumption on the observed covariates conditional on α_h is maintained although the arbitrary correlation between the two is allowed in this case. This implies that the observed covariates only contain time varying explanatory variables.

Table 3 Regression results—determinants of crop riskiness per farm household using the risk index measure

	Random effects specification			Mundlak-Chamberlains Fixed Effects specification		
	(1)	(2)	(3)	(1)	(2)	(3)
Age	−0.001***	−0.001***	−0.001***	0	0	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender	−0.056***	−0.057***	−0.055***	−0.050***	−0.050***	−0.049***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Number of male adults in household	0.039***	0.039***	0.038***	0.068***	0.068***	0.068***
	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)
Number of female adults in household	0.053***	0.053***	0.053***	0.093***	0.094***	0.094***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
Write	0.028***	0.026**	0.029***	0.027***	0.028***	0.028***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Number of livestock	0.003***	0.003***	0.003***	0	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of oxen	−0.003***	−0.003***	−0.003***	0	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total land area by hh	0	0	0	0	0	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg_red	−0.073***	−0.071***	−0.070***	−0.067***	−0.068***	−0.064***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Avg_white	−0.117***	−0.113***	−0.113***	−0.100**	−0.095**	−0.096**
	(0.040)	(0.040)	(0.040)	(0.039)	(0.039)	(0.039)
Avg_flatslop	−0.067***	−0.064***	−0.061***	−0.064***	−0.061***	−0.058***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Avg_fertile	0.032***	0.027**	0.032***	0.024**	0.023*	0.023**
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Kebele	−0.015***		−0.016***	−0.013***	−0.014***	−0.014***
	(0.002)		(0.003)	(0.002)	(0.003)	(0.003)
Long term average annual rainfall	0		0.000**	0		0.000**
	(0.000)		(0.000)	(0.000)		(0.000)
Long term average spring rainfall		0	−0.002***		−0.001	−0.001**
		(0.000)	(0.001)		(0.000)	(0.001)
Long term average summer rainfall		0.001***	0		0	0
		(0.000)	(0.000)		(0.000)	(0.000)
Mfemale				−0.071***	−0.072***	−0.072***
				(0.009)	(0.009)	(0.009)
Mmale				−0.047***	−0.047***	−0.047***
				(0.009)	(0.009)	(0.009)
Mox				−0.010***	−0.009***	−0.009***
				(0.002)	(0.002)	(0.002)
Mlivestock				0.010***	0.009***	0.009***
				(0.002)	(0.002)	(0.002)
Constant	0.489***	0.205***	0.620***	0.506***	0.556***	0.612***
	(0.041)	(0.044)	(0.092)	(0.041)	(0.088)	(0.091)
N	5,339	5,339	5,339	5,339	5,339	5,339
Chi2	1546.12	1555.43	1616.46	1,500	1,501	1,501
Prob>Chi2	0	0	0	0	0	0

Significance levels are denoted by one asterisk (*) at the 10 % level, two asterisks (**) at the 5 % level and three asterisks (***) at the 1 % level

Village level dummies are used as controls for differences in village level characteristics

Table 4 Regression results—determinants of crop riskiness per farm household using risk ranking measure

	Random effects specification			Mundlak-Chamberlains Fixed Effects specification		
	(1)	(2)	(3)	(1)	(2)	(3)
Age	−0.001*	−0.001*	−0.001*	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	−0.113***	−0.115***	−0.111***	−0.098***	−0.099***	−0.096***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Number of male adults in household	0.057***	0.057***	0.056***	0.051***	0.052***	0.051***
	(0.007)	(0.008)	(0.007)	(0.012)	(0.012)	(0.012)
Number of female adults in household	0.065***	0.063***	0.066***	0.100***	0.100***	0.101***
	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)
Write	0.046***	0.039**	0.048***	0.040**	0.040**	0.042**
	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)
Number of livestock	0.006***	0.007***	0.006***	−0.001	−0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of oxen	−0.006***	−0.007***	−0.006***	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total land area by hh	0	0	0	0	0	0
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Avg_red	−0.087***	−0.084***	−0.079***	−0.091***	−0.096***	−0.084***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)
Avg_white	−0.143**	−0.139**	−0.139**	−0.138**	−0.129*	−0.133**
	(0.067)	(0.067)	(0.067)	(0.067)	(0.066)	(0.066)
Avg_flatslop	−0.066***	−0.063***	−0.057**	−0.069***	−0.069***	−0.060***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Avg_fertile	0.036*	0.025	0.036*	0.037*	0.035*	0.037*
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Kebele	−0.039***		−0.044***	−0.037***	−0.039***	−0.040***
	(0.004)		(0.006)	(0.004)	(0.006)	(0.006)
Long term average annual rainfall	0.000*		0.000***	0.000**		0.000***
	(0.000)		(0.000)	(0.000)		(0.000)
Long term average spring rainfall		0.002**	−0.003***		0	−0.002**
		(0.001)	(0.001)		(0.001)	(0.001)
Long term average summer rainfall		0.003***	−0.001**		0	−0.001
		(0.000)	(0.001)		(0.000)	(0.001)
Mfemale				−0.071***	−0.071***	−0.070***
				(0.015)	(0.015)	(0.015)
Mmale				−0.008	−0.008	−0.009
				(0.015)	(0.015)	(0.015)
Mox				−0.027***	−0.025***	−0.026***
				(0.004)	(0.004)	(0.004)
Mlivestock				0.027***	0.025***	0.026***
				(0.004)	(0.004)	(0.004)
Constant	0.930***	0.084	1.232***	0.909***	0.995***	1.160***
	(0.072)	(0.079)	(0.162)	(0.072)	(0.156)	(0.162)
Wald chi2(24)	1044.91	1117.4	1127.63	1108.94	1109.40	1109.64
prob>chi2	0	0	0	0	0	0

Significance levels are denoted by one asterisk (*) at the 10 % level, two asterisks (**) at the 5 % level and three asterisks (***) at the 1 % level characteristics are comparatively significant predictors of risk compositions of crop choice. Households are less likely to select a less risky crop portfolio if the proportion of plots with red soil colour owned is high, possibly due to very high water retention capacities of such plots. Households with a high proportion of fertile and steeper slope lands also tend to have overall high levels of riskiness in their crop mix.

In Table 4, we present the results from the random effects and Chamberlain-Mundlak random effects estimations using risk ranking (instead of the risk index used in Table 3), as the dependent variable. Most of our results are consistent across the different specifications, showing limited effects of unobserved heterogeneities and measurement of the dependent variable on our parameter estimates. The regression results confirm that both annual and seasonal rainfall means have significant impacts on the choice by farm households of the riskiness of their crop portfolios.

Conclusions

Rainfall variability is one of the most important sources of uncertainty in agricultural production in Ethiopia. Farmers need a better understanding of production risk and its management in order to inform their decision making process. This paper explores the choice of a combination of crops as an ex ante risk management mechanism when crop insurance is limited or non-existent. Our central premise is that in a multicropping system, the combination of crops chosen is likely to be sensitive to weather measured by annual, summer and spring rainfall variability. Inter-crop interaction effects within a farm can also be an important driver of this choice. We therefore computed riskiness of crop portfolio choice by farm households using the Single-Index Method and explored its link to weather variability.

Based on a plot level panel data set from Ethiopia, the results indicated that the level of riskiness of crop portfolio is partly motivated by rainfall variability, particularly that of annual and summer rainfall. In the context of our case study, we find that, in many cases, moisture sensitive crops tend to have high beta coefficients, although for some crops this pattern does not hold. This finding may be driven in large part by tendencies to rely on less moisture sensitive crops in times of rainfall shortages and vice versa. The relatively narrow dispersion of the risk index, at farm level, points to the tendency of households to combine risky and less risky crops and the importance of taking into account crop interdependencies in analysing overall riskiness.

As long as successful coverage of crop insurance remains limited or non-existent, using crop and technology choices remain the most efficient way of shielding against weather related production risks. However, the costs associated with traditional agricultural risk programs could be large. Future research, which investigates the costs of using such insurance mechanisms against exogenous factors, would lead to a proper understanding of the risk management needs of farmers operating in extremely risky environments.

The finding that crop riskiness at a farm level is highly responsive to rainfall variability and that the choice of high risk—high return crops is hampered by weather uncertainty have important implications for policy. First, development policy initiatives aimed at encouraging investment and asset accumulation need to look not only into credit and off farm policies but also into weather insurance policies. Furthermore, with the impacts of climate change on small holder agriculture and increasing efforts to mainstream climate change policy, crop insurance could be one area where climate policy could be effectively linked to development policy. Second, agro-biodiversity conservation efforts could effectively target high rainfall uncertainty areas. Higher riskiness of the crops (leading to higher expected return) is expected to increase yield, and increase overall income of households. However, actually quantifying to what extent riskiness of crops leads to a gain in productivity and to what extent that gain is compromised by weather uncertainty merit further analysis. Furthermore, there will be costs associated with portfolio change if households decide to alter their crop composition in response to weather variability or for other reasons. These include acquiring new seeds, learning new techniques, as well as adapting plots and cultivation techniques to the new crops. Further studies need to look into the quantitative relationships between the gains in productivity and the costs of such adjustments. In addition, extension of this analysis to include investment (such as livestock) and non-farm income choices would allow a more comprehensive understanding of the possibilities of income diversification.

Appendix: The single index method measuring the riskiness of crop portfolio at the household level

Equation 1a specifies the relationship between the reference portfolio revenue, and the individual crop revenue

$$S_K = \sum_{i=1}^{n} x_i S_i \tag{1a}$$

Where S_k is the reference portfolio, X_i is the weight of enterprise (crop) i, and S_i stand for the stochastic revenue of crop i.

Similarly, the revenue variance-covariance relationships between the reference portfolio and the individual crop revenues are given by:

$$z_K^2 = \sum_{j=1}^{m} \sum_{i=1}^{n} d_i d_j z_{ij} \tag{2a}$$

where ${z_K}^2$ is variance of the revenue corresponding to the reference portfolio, z_{ij} and the covariance of the individual crop revenues. This equation captures the essence of the single index method—that the portfolio risk measures the proportionate contribution of an individual enterprise's risk to the variance of the underlying index.

From Eq. 2a, the marginal risk—the contribution that each crop makes to portfolio variance is computed. This is given by:

$$\frac{\partial V_K^2}{\partial x_i} = 2\sum_{j=1}^{n} d_i V_{ij} \tag{3a}$$

Our parameter of interest, the anticipated changes in the revenues of a commodity in response to changes in portfolio returns, beta, is given in Eq. 4a.

$$\beta_i = \frac{z_{ij}}{z_k^2} \tag{4a}$$

This parameter is retrieved from regressions of S_{ih} on the underlying reference portfolio, S_{kh}, are the characteristic equations that determine systematic and non-systematic risk

$$S_{ih} = \alpha_i + \beta_i S_{kh} + e_{ih} \tag{5a}$$

Where α_i is the intercept and β_i is the regression coefficient, and e_{it} is the error term. For simplicity, the weights d_i are kept to 1 (equal weights).

The beta parameter estimated then measures the riskiness of each crop. Averaging over the beta coefficients estimated for each crop within the household gives the riskiness of the overall crop portfolio of the household.

In Turvey (1991), the basis of the empirical approach for our paper, the unit of analysis in their study is the county. Therefore, Eq. 5a is estimated using time-series data to generate, a county-beta. In our case, as we set out to estimate beta for each crop within the household, our unit of analysis is essentially the plot (crop type) within each household, for which we have a plot level observations for about 1,500 households over the four survey years. As a result, unlike Turvey (1991) OLS estimation of Eq. 5a using time series data, our estimation is an estimation of panel data (time subscripts representing years are suppressed for notational convenience). In order to take advantage of the panel feature of our data, (and to circumvent the effect of the beta coefficient picking up the effect of variation across households), we estimate Eq. 5a using a household fixed effects estimator.

In sum while we have the advantage of larger numbers of observations across households, our panel is short making time series estimation impossible. It should be noted that using time series data for such estimations is difficult in our setting and we are not aware of any such data at the plot level in a multicropping farm context in Ethiopia. Even our detailed plot level data collected over 4 years is very rare. This is the first step in trying to measure riskiness using this methodology. Future studies need to look into using much richer sources of data.

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